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ABSTRACT

The Goodman technique of log linear analysis is ideal for family research, because it is designed for categorical (non-quantitative) variables. Variables are dichotomized (for example, married/divorced, childless/with children) or otherwise categorized (for example, level of permissiveness, life cycle stage). Contingency tables are then constructed and analyzed so that variables are cross-classified; estimates of the main effects of each variable, as well as interaction effects, are determined. This technique permits sophisticated (multivariate) analysis of quantitative data, testing of interactions, and examination of the relationships among variables, without designating one as the dependent variable. There are limitations to the Goodman technique, associated with the principal statistics used (Pearson's Chi-square and the likelihood ratio statistic), and with categorizing variables. Logit analysis, a type of log linear analysis, is used to predict a dependent variable. First, the relative importance of race, sex of family head, and life cycle stage in predicting the dependent variable, financial expectation, is examined; second, interaction effects are measured, that is, the existence of a conditional relationship among two or more predictor variables and the dependent variable. The best prediction model included the direct effects of life cycle stage and sex of breadwinner. (CP)

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Using Log Linear Analysis for Categorical Family Variables[1]

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Abstract

This paper introduces an innovative statistical technique: Goodman's Log Linear Analysis. This procedure is particularly appropriate for researchers in the family area since it is designed for categorical data and so many of the family variables are categorical. Both the strengths and weaknesses of log linear analysis are discussed. Logit analysis, a special form of log linear analysis with a dependent variable is described. An example of logit analysis, looking at family breadwinners' financial expectations (using data from the Michigan Panel of Income Dynamics), is given.

Introduction

Much of the subject matter of family social scientists involves categories of attributes. Characteristics of families--one-parent, two-parent; middle class, working class; authoritarian, egalitarian--and characteristics of family members--sense of efficacy, sexual attitudes, parental values--are difficult to quantify as interval level data. What is needed is a methodology that can handle categorical variables. Fortunately such a technique exists: Goodman's method of log linear analysis (see, for example, Goodman, 1970, 1972). This paper will provide an overview of this method of analysis of multi-dimensional contingency tables, demonstrating its utility for the family social scientist.

When the dependent variable is quantitative, the researcher can use well known techniques of multivariate analysis (regression, analysis of variance, correlation). But to use these tools with a categorical dependent variable requires violating key assumptions. The procedure discussed here requires no such violations.

Log Linear Analysis: Overview

Analysis of cross-tabulated data is familiar to most family researchers. It involves the examination of two-way and three-way tables in order to discern patterns of relationships among variables (for examples of contingency table analysis, see Rosenberg, 1968).

The form of analysis discussed here is a method of multivariate categorical data analysis, the fitting of log linear models to multi-dimensional contingency tables (for a discussion of categorical data

analysis, see Goodman, 1970, 1971, 1972; Fienberg, 1977). Log linear analysis is in essence a generalization of testing for interaction in a bivariate contingency table. It permits one to evaluate bivariate and higher order relationships by controlling for other variables and thus provides a more precise understanding of the nature of multivariate relationships. When the relationship between two variables is dependent on a third, all three variables are said to interact. This technique of fitting log linear models is designed to easily study interactions.

It is also designed for categorical variables. Many of the variables used in family research are categorical (for example, presence/absence of children, marital satisfaction, violence, employed wife, etc.). In a contingency table, variables are cross-classified and estimates of the main effects of each variable as well as the interaction effects between the variables are computed. The aim is to find a model which fits the data. The best-fitting model is one that can best estimate the cell frequencies by using the fewest number of parameters. The objective is a statement which adequately summarizes the data.

When the concern is predicting a particular dependent variable, logit analysis, a special form of log linear analysis is used. Logit analysis involves the use of a number of descriptive attributes--variables in a contingency table--to estimate the frequency of one category of the dependend variable. The logit technique provides measures of association between each predictor variable and the criterion variable (direct effects). These measures tell to what extent knowledge of the predictor

variable enables one to estimate the category or categories of the dependent variable. We can also obtain information on interaction effects, which measure the existence of conditional relationships among two or more predictor variables and the dependent variable.

Logit analysis can best be understood through the use of an example. For instance, we find that black families with children are more susceptible to unemployment of the breadwinner than are white families with children. Can this relationship be explained by introducing various environmental, occupational, or personal characteristics? What is it about these families that accounts for their higher susceptibility to the stressor, unemployment? Logit analysis enables us to separate out the various effects of a number of variables on the categorical dependent variable, unemployment.

It also provides a measure of the effects (logits), estimates of that portion of variance in the dependent variable that can be "explained" by each of the predictor variables. Both logits and odds ratios provide a means of assessing the contribution and direction of each variable. Logits are logarithms of multiplicative odds ratios and are therefore additive. A logit of zero means that the parameter has no effect in estimating the criterion variable. Odds are multiplicative; odds of 1.00 means there is a 50:50 chance that the dependent variable will fall into one category or another. In other words, an odds ratio of 1.00 says our predictability on one variable is not at all improved by our knowledge of a particular independent variable.

The sign of the logit shows the direction of the effect of the predictor on the criterion variable. Similarly, odds greater or less than 1.00 show the strength of the relationship between variables. To gauge the comulative effects of a number of parameters, one can either sum the logits or multiply the odds ratios.

Both logits and odds ratios are usually included in the data analysis. Logits are analogous to the more familiar betas in multiple regression analysis and their additive qualities make them easier to work with. But odds ratios make more "sense;" they are easier to interpret than are logits.

The "Goodman" approach to log linear (logit) analysis is particularly appropriate for research problems in the family area since the dependent variable is often categorical and since a number of interactions between family structure and other family and individual variables are often built into the hypothesized relationships. As has been pointed out, interaction effects have often been ignored in social science research because they are "hard to handle" in many statistical procedures (Davis, 1972:37).

However, there are several limitations to the log linear technique. First, it requires the data to be grouped into discrete categories, dichotomies being the simplest and most convenient. Discretizing certain interval ordinal level continuous independent variables results in a loss of information. Second, the principal statistics used in the analysis, Pearson's chi-square (X^2) and the likelihood ratio statistic (LRX^2), are particularly sensitive to sample size; large samples may produce significant chi-square statistics even when the size of the effects are small

(for a discussion of the problems of log linear analysis, see Reynolds, 1977). Finally, since this method involves the use of multidimensional contingency tables, even with a large sample there is the problem of zero cells. (However, this problem is not unique to log linear analysis. It exists in all statistical analysis.)

In spite of these difficulties, the model building technique of log linear analysis has advantages over other statistical procedures for the family social scientist because it provides the best mechanism for estimating the frequency of categorical outcomes. It is also the best method for specifying the nature of the distributions of a categorical variable through the use of control variables. In addition, no direct assumptions have to be made about the correlation of the independent variables, homoscedasticity, or about a normal distribution.

Interpreting Log Linear Analysis

The goal of logit analysis is to construct a model using the predictor (independent) variables that will estimate cell frequencies of the dependent variable.

Chi-square random variables are used to measure the goodness of fit of various models. Two measures are frequently used, Pearson's (X^2) and the likelihood ratio statistic (LRX^2). The formula for the Pearson's chi-square is:

$$X^2 = \Sigma \frac{(\text{Observed} - \text{Expected})^2}{\text{Expected}},$$

comparing all the observed cell frequencies to the expected cell frequencies generated by the particular model used. The formula for the likelihood ratio statistic is:

$$LRX^2 = 2 \Sigma (\text{Observed}) \log \frac{(\text{Observed})}{(\text{Expected})}.$$

This measure is also computed using the observed and expected cell frequencies. The degrees of freedom associated with the chi-square random variables are determined by the following formula:

d.f. = # cells minus # parameters fitted.

For cells with zero frequencies, there are special formulas for adjusting the degrees of freedom (see Fienberg, 1977, Chapter 8).

What is required is a model that is not significantly different from the data. For that reason, chi-squares that are not significant are sought. To test the "fit" of models, the Pearson statistic (X^2) provides the best measure. To compare differences to fit between models, the likelihood ratio chi-square is used (LRX^2). (See discussions in Goodman, 1971, 1972; Fienberg, 1977.) The p-value appropriate to the degrees of freedom is used to appraise the goodness of fit and the improvement of fit between models. A type-I error rate of .05 is the criterion usually used; models with p-values less than the type-I error rate ($p < .05$) are thrown out.

Goodman (1972) and Fienberg (1977) suggest two methods of assessing the value of an independent variable or variables in predicting the criterion variable. One method is essentially a process of elimination, starting with the saturated model, that is, an equation including all possible combinations of parameters. By analyzing the standardized "effects" the relative contribution of each variable can be guaged. The second technique involves a forward process of hypothesis testing, measuring the relative significance of each parameter through evaluating differences in chi-square statistics as a consequence of the delection or addition of a

variable or interaction term. Both methods have their drawbacks (and advantages, see Goodman, 1972, 1973).

The advantage of the forward process is that it permits a systematic testing of variables, and hence, hypotheses concerning the relationships between various independent variables and the dependent variable. This method will be used in the example which follows.

A standard procedure is followed in this model fitting process. First, a model of independence is tested--to see if there is any relationship between the criterion variable and the independent (predictor) variables. If there is a significant difference between the expected frequencies and the actual frequencies of the data ($p < .05$) then models of direct effects and interaction effects are tested.

The relationships between the independent variables are "held constant" by including a parameter accounting for them in every model fitted. For example, in looking at the distribution of unemployment by race and sex, the relationship between race and sex is of no interest; nevertheless, it is incorporated in the model fitting process.

Once a model is found that fits the data (p-value greater than .05), then parameters are systematically removed to find the most parsimonious model. The likelihood ratio statistic (LRX^2) is used to measure the significance of each deleted value; in this case, we are looking for significance in the p-value (less than .05). Parameters which are significant are usually important in the model. The differences between the likelihood ratio statistic of the basline model and the likelihood ratio statistic of a model with a missing variable is actually a coefficient of

partial determination (Goodman, 1972:1056-1058). The greater this coefficient, the greater the relative importance of that variable in predicting the criterion variable. Once the "best-fitting" model is found, then the logits and odds are given. These represent the improvement in estimation resulting from each parameter included in the model.

Summary of Procedure

The steps of analysis in using the logit form of log linear analysis are as follows:

1. Fit several descriptive and/or explanatory variables in a logit model to test for interaction and the relationship between these variables and the criterion variable, and find a model which is not significantly different from the data ($p > .05$).
2. Systematically remove parameters from the fitted model to see which variables are important predictors of the criterion variable (p-value $< .05$). Include the significant parameters to find the most parsimonious, "best-fitting" model.
3. Examine the logits and odds of the parameters of the best-fitting model to determine the direction and strength of the effects of each independent variable, conditioning on to others.

An Example

An important aspect of a family's financial position is the subjective "definition of the situation" component. To tap this dimension of family economic well being responses of family breadwinners to the following question were evaluated:

> "What about the next few years, do you think you (and your family) will be better off or worse off or what?"

In the context of the actual interview this question follows a series on the economic situation of the family. The data is from the 1976 series on the economic situation of the family. The data is from the 1976 wave of the Michigan Panel Study of Income Dynamics and involves a sample of black and white heads of families with children under 18 (for a fuller description of the research, see Moen, 1978).

Do breadwinners of families at different life cycle stages have different expectations concerning the family's financial future? Are male heads of households more optimistic or pessimistic concerning the financial outlook of the family? Do economic expectancies vary by race? To answer these questions requires the analysis of a multidimensional contingency table. We therefore will use logit analysis to describe the likelihood that family heads of different types will expect their family's financial future to decline over the next few years. We fit a model using the following characteristics: race, sex of head, and family life-cycle stage. The "dependent" variable has been dichotomized as the response to the above question, categorized as:

Financial	0)	better or the same
Expectancy	1)	worse off

Other variables included in this model are categorized as follows:

Race	1)	white
	2)	black
Sex of Head	1)	male
	2)	female
Life-cycle	1)	youngest child under 6
Stage	2)	6 through 12 years
	3)	13 to 18 years

Logit analysis provides us with a mechanism for determining the relative importance of each of these characteristics in estimating the bread-winner's definition of the family's future financial situation.

A sample model estimating the probabilty (or odds) of family heads having a negative financial outlook using the logit form of log linear analysis is presented below.

Equation 1 $$\Phi_{\bar{e}} = B^{\bar{e}} + B^{r\bar{e}}_{i} + B^{s\bar{e}}_{j} + B^{l\bar{e}}_{k}$$

Equation 1 represents a model using the logs of the estimated probability of financial expectancy and not including interaction effects among the variables where:

$\bar{e}$ = financial expectancy (the family will be worse off)

r = race

s = sex

l = life cycle stage

Equation (1) states that the log of the expected odds of unemployment (Φ_{e}) can be expressed as a sum of the effects of the general mean of the incidence of negative expectations ($B^{\bar{e}}$) plus the direct effects of the race ($B^{r\bar{e}}$) and the direct effects of sex of the family head ($B^{s\bar{e}}$) and life-cycle stage ($B^{l\bar{e}}$).

Equation (2) represents a model which includes two interaction effects.

Equation 2 $$\Phi_{\bar{e}} = B^{\bar{e}} + B^{r\bar{e}}_{i} + B^{s\bar{e}}_{j} + B^{l\bar{e}}_{k} + B^{rs\bar{e}}_{ij} + B^{sl\bar{e}}_{jk}$$

This states the same relationships as depicted in Equation 1, but includes two interaction parameters which depict the odds of negative expectancy as a consequence of both main effects (discussed above) and the interaction effects of sex and race ($B^{rs\bar{e}}_{ij}$) and sex and life cycle stage ($B^{sl\bar{e}}_{jk}$).

The analysis in this example entails a process of fitting equations such as these to the data in order to arrive at the best model for estimating each of the criterion variables (for cross-classification data see Table 4 in appendix).

The first model tested is one of independence, of no relationship between these variables and the dependent variable, financial expectations. As we can see in Table 1, this model (H_0) does not fit the data. Next,

---

Insert Table 1 about here

---

we fit a model of direct affects (H_1). This model suggests that each characteristic has a direct effect on the breadwinner's financial outlook but that there are no indirect effects, no interactions in the data. The direct effects model (H_1) fits the data ($p > .05$). We turn, therefore, to a further analysis of the direct effects model to see if it is the best fitting model or if additional parameters can be deleted to simplify the picture. The results are given in Table 2.

Insert Table 2 about here

Table 2 reveals the relative unimportance of race in fitting a model describing the distribution of financial expectations. In other words, controlling for life-cycle stage and sex of the family head, there is no difference in the financial outlook of white and black breadwinners. The "best fitting model" then is one that includes the direct effects of life-cycle stage and sex of the breadwinner. To see the relative importance and direction of the effects of these characteristics, we can examine the logits and odds ratios (Table 3).

Insert Table 3 about here

Looking at Table 3 we see that the likelihood of expecting to be worse off financially does differ--but not markedly so--across life-cycle stage and by sex of the family head. Controlling for sex, we find a positive relationship between life-cycle stage and negative expectations. Heads of families at stage one are more likely to feel their financial future will be better or the same (odds = .76). Heads at stage two have an even chance thinking things will be worse (odds = 1.02). Heads of families at stage three are relatively more prone to negative financial expectations (odds = 1.29).

Controlling for life-cycle stage, we find that male family heads are slightly less likely (odds = .85) to be pessimistic about the families' financial future than are women breadwinners (odds = 1.17).

Logit analysis has shown that, controlling for life cycle stage, women breadwinners are more prone to having a negative outlook on their family's financial future than are male breadwinners. Both men and women heads of households are least likely to be pessimistic about the future finances of the family at the early stages of the life-cycle. Figure 1 shows the variations in logits by sex and family life cycle stage.

Insert Figure 1 about here

The Goodman technique has demonstrated that there are no interaction affects among the predictor variables in estimating the dependent variable, financial expectancy. In other words, women who head families with a child under six (stage one) are no more likely to have negative expectations than would be estimated by knowing the separate effects of both sex

and life-cycle stage. Logit analysis has also demonstrated that race is not a good predictor of financial expectancy once life-cycle stage and sex are controlled for (that is, taken into account). Race is conditionally independent of expectancy, given sex and life-cycle stage (1,2|3,4). In other words, both black and white family heads of the same sex have the same odds of expecting the family to be worse off at each life cycle stage.

Conclusions

The Goodman technique of log linear analysis is designed for categorical variables. Variables are dichotomized (e.g., married/divorced; childless/with children; black/white) or otherwise categorized (for example, levels of permissiveness, life-cycle stage). Contingency tables are then constructed and analyzed. ~~In a contingency table~~ so that, variables are cross-classified and estimates of the main effects of each variable as well as interaction effects are determined.

The greatest advantage of the log linear technique for the family social scientist is that it permits a sophisticated (multivariate) analysis of qualitative data. ~~A second advantage is that~~ it provides for the testing of interactions. Another asset involves the ~~ability to~~ examination of the relationships among variables without designating one as the "dependent" variable.

But there are problems with the Goodman technique. Variables must be categorized; therefore information is lost when an interval level variable (such as number of children) is dichotomized (for example: (1) one or two children, (2) three or more children). The manner in which these variables are categorized can also affect the log linear reuslts (for

example, we can look at families with one one child versus all other families and very probably get different results than when we look at families with at least two children as opposed to larger size families. An additional drawback is the problem of zero frequencies in cells as the number of variables and/or categories increases.

Overall, however, the development of this technique of categorical analysis offers much promise for the fuller understanding of family data. Decisions concerning the appropriateness of log linear analysis can be based on the following considerations:

1) Types of variables and their relationships. If variables are categorical (especially the dependent variable) or if independent variables are not statiscally independent, log linear analysis would be a good technique to use. If one is concerned with the patterning of relationships among variables rather than one dependent variable, log linear analysis is excellent. If one hypotheses interactions among variables, log linear analysis is first rate.

2) Number of variables. Log linear analysis can be used on any number of variables but gets difficult to interpret with more than six or seven variables. Moreover, as the number of variables increases, the problem of zero cells increases. A rule of thumb is that the number of cases divided by the number of cells should be 5 or greater.

A final consideration in the selection of analytic procedures is that we tend to feel most comfortable with the familiar and multiple regression that is familiar to many of us. But regression and log linear analysis are analogous techniques (see Magidson, 1978) and should produce similar

results if the data is not badly skewed, there are no interactions, and there is no multicollinearity. If these conditions are true why not try both procedures? Then when these conditions do not hold and log linear analysis is most appropriate, it will not be an unknown quantity.

Table 1

Models Estimating (1)Financial Expectations[1] of Family Breadwinners by (2)Race, (3)Sex and (4)Life Cycle Stage[2]

Model	Parameters Fitted	Description	Pearson Chi-square (X^2)	Likelihood Ratio Chi-square (LRX^2)	Degrees of Freedom	p-value
H_0	[1] [234]	no effects	52.34	52.88	11	$p < .05$
H_1	[234] [12] [13] [14]	direct effects	11.46	11.47	7	$p > .05$

[1]Response to question: What about the next few years, do you think you (and your family) will be better off or worse off or what?

[2]Age of Youngest Child (stage 1 = under 6 years; stage 2 = 6-12 years; stage 3 = 13-18 years)

Source: Michigan Panel Study of Income Dynamics, 1975 wave

Table 2

Tests of Relationship of Family and Individual Characteristics[1] and Financial Expectations[2] of Family Breadwinners

Model	Parameters Deleted	GOODNESS OF FIT LRX^2	d.f.	p-value	IMPROVEMENT IN FIT LRX^2	d.f.	p-value
H_0 [12] [13] [14][234]		11.47	7	$p > .05$			
H_1	-[12] (race)	14.14	8	$p > .05$	2.67		$p > .05$
H_2	-[13] (sex)	17.14	8	$p < .05$	5.67		$p < .05$
H_3	-[14] (life cycle stage)	37.18	9	$p < .05$	25.71	2	$p < .05$

[1] Variables included in the model:
1 = financial expectations (0=future same or better; 1=future worse)
2 = race of head (1=white; 2=black)
3 = sex of head (1=male; 2=female)
4 = life cycle stage [age of youngest child](1=under 6 years; 2=6-12 years; 3=13-18 years)

[2] Response to question: What about the next few years, do you think you (and your family) will be better off or worse off or what?

Source: Michigan Panel Study of Income Dynamics

Table 3

Measures of Effects of Selected Variables[1] Stage on the Financial Expectations of the Family Breadwinner

Parameters Included in the Model	Variable Name	Level	Logits*	Odds Ratios
[13]	sex of head	male	-.158	.85
		female	.158	1.17
[14]	life-cycle stage (age of youngest child)	stage 1 (under 6)	-.270	.76
		stage 2 (6-12)	.018	1.02
		stage 3 (13-18)	.252	1.29

*positive sign means increased likelihood of expecting financial situation to get worse

[1]Variables included in the model:
1 = financial expectations (0=future same or better; 1=future worse)
2 = race of head (1=white; 2=black)
3 = sex of head (1=male; 2=female)
4 = life cycle stage [age of youngest child](1=under 6 years; 2=6-12 years; 3=13-18 years)

Source: Michigan Panel Study of Income Dynamics

TABLE 4
Cross-classification* of Financial Expectations of
Family Breadwinners by Race, Sex and Life Cycle Stage

Race	Sex	Life Cycle Stage**	Financial Expectations Things will get: Better/same	Worse
White	Male	Stage 1	508	185
White	Male	Stage 2	268	165
White	Male	Stage 3	135	107
White	Female	Stage 1	18	15
White	Female	Stage 2	41	19
White	Female	Stage 3	23	19
Black	Male	Stage 1	249	126
Black	Male	Stage 2	126	69
Black	Male	Stage 3	42	31
Black	Female	Stage 1	128	88
Black	Female	Stage 2	92	77
Black	Female	Stage 3	48	41

*Source: Michigan Panel Study of Income Dynamics, 1975 wave - unweighted sample of breadwinners of families with children under 18 (N = 2642).

**age of youngest child (1 = under 6 years; 2 = 6-12 years; 3 = 13-18 years)

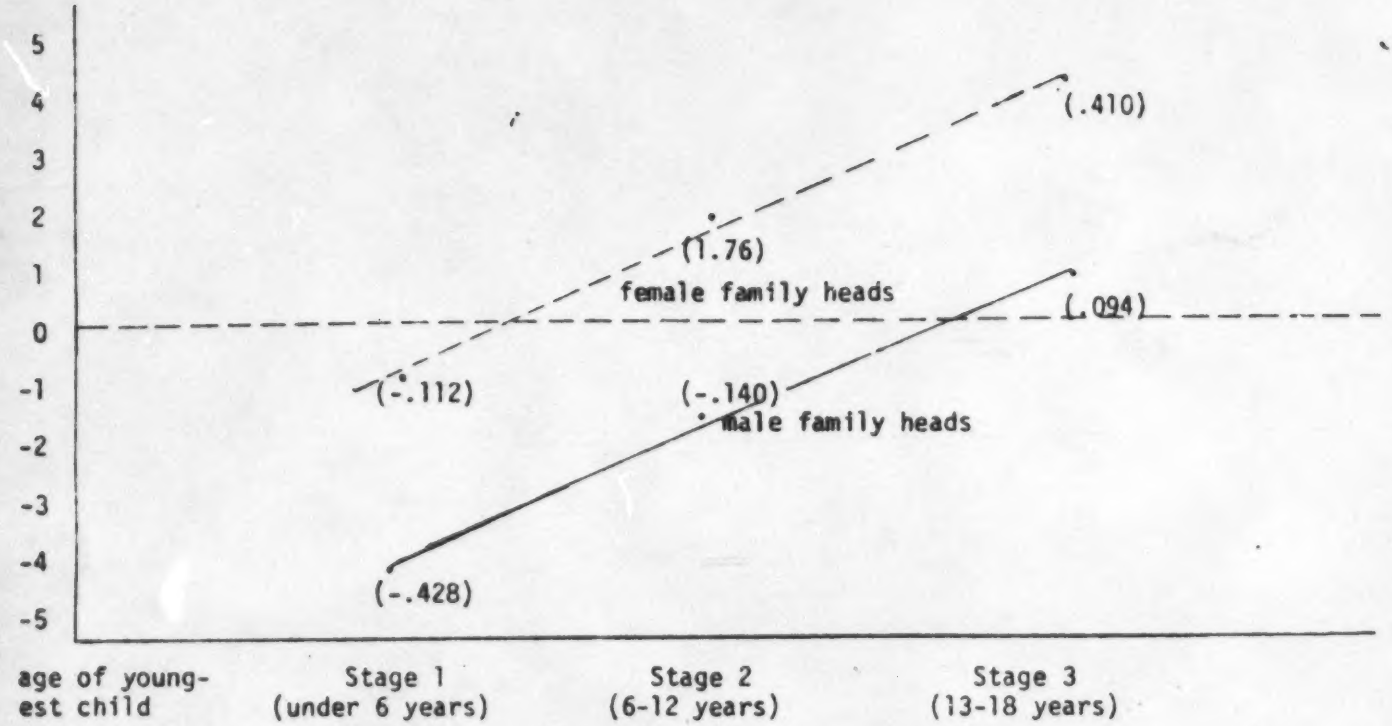

Figure 1

Logits of Financial Expectanct of Family Breadwinners by Sex and Life-Cycle Stage [1]

[1] positive sign means increased likelihood of expecting financial situation to get worse

source: Michigan Panel Study of Income Dynamics 1975 wave
subsample of heads of families with children under 18 (N = 2642)

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